1. Summary Information Page

Proposal To:

Utah Division of Air Quality

Science for Solutions Research Grant – FY 2023

Project Title:

Improving smoke detection and quantifying the wildfire smoke impacts on local air quality using modeling and machine learning techniques

Applicant Information:

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Funding Requested:

A total of **$61,738** is requested

Project Period:

1 July 2022 – 31 June 2023

2. Scope of Work

2.A Abstract

As one of the major emissions sources in the western U.S., smoke from wildfires is emitted to the atmosphere and transported downwind based on unique meteorological and topographical conditions[1]. Due to the difficulties of direct measurement, it remains a challenge to quantify the air quality impacts from wildfire smoke[2, 3]. For example, a small human-caused wildfire occurred in Parley Canyon, Utah on August 14, 2021. The smoke plume was released into the atmosphere (Figure 1(A)), thousands of homes were evacuated and the air quality in Salt Lake City on the following days was significantly worse than usual (Figure 1(C) and (D)). Around the same time, California wildfires (Figure 1 (B)) emitted smoke with large amounts of pollutants, also contributing to unhealthy air quality in Salt Lake City (Figure 1(C) and (D)). Both fires caused increased in ozone concentrations which indicates that secondary air pollutants are strongly affected by wildfire smoke. Though it is easy to tell that wildfire smoke has negative impacts on urban air quality from Figure 1, there is no tool to quantitatively measure wildfire impacts, nor to identify whether exceedance days are due to wildfire smoke or other emissions.

Figure 1 *(A) Smoke plume from the wildfire in Parleys Canyon, Utah on 14 Aug. 2021. (B) NOAA GOES-17 visible image of smoke from the Dixie Fire in California on 6 Aug.2021. (C) Daily PM2.5 and (D) 8hr ozone concentrations and the corresponding air quality index (AQI) in Salt Lake City for August 2021. Blue boxes in panels C and D refer to the two smoke events are shown in panels A and B*

Transport of wildfire smoke plumes is a complex process, especially in intermountain areas[4, 5]. Differentiating the impacts of wildfire smoke from other emissions is also difficult because the current observations are not able to directly identify the source of pollutant species. Many plume rise models have been used to represent the distribution of smoke in vertical layers and are implemented into the chemical transport model (CTM) framework to estimate smoke emissions and transport[6-8]. But the accuracy is limited by uncertainties in representing meteorological conditions, planetary boundary layer (PBL) conditions and fire intensity[9, 10]. Surface temperatures, wind speeds, atmospheric turbulence and other impact factors of complex mountain terrain make it challenging to accurately describe surface atmospheric dynamics during fire episodes. Surface meteorological conditions over mountains are not well estimated because the empirical formulas were developed for flat, uniform terrain[11-13]. As a result, the surface turbulence that impacts PBL and plume injection heights are not accurately represented in mountain areas. New models are necessary to improve the simulation of plume rise and better estimate downwind smoke concentrations[14]. **The first scope (S1) of this work will develop a new plume rise model to estimate the plume injection heights for larger wildfires, which will improve simulations of smoke transport and downwind air pollution concentrations.**

Air quality measured by many real-time monitoring networks[15]. With monitoring data, several areas along the Wasatch Front are classified as nonattainment areas by U.S. EPA[16, 17]. However, no technique can directly identify and quantify wildfire smoke impacts based on observations[18, 19]. Model simulations can be used to fill this gap. Many source apportionment techniques are available to investigate the relationship between high ozone pollution and wildfire activities during summer[20-22]. But complex interactions between wildfire emissions and the urban environment result in uncertainties in model performance during fire season[23, 24]. Major pollutants in wildfire smoke, NO_x and VOCs, can significantly affect urban atmospheric chemistry as a result of the presence of wildfire smoke and interactions with urban emissions[25-27]. Such changes include the switch of the dominant ozone precursor regime. Heat energy from smoke also changes urban climatology which can modify the photochemistry. Complex atmospheric urban physical and chemical dynamics make model simulation difficult to accurately describe wildfire smoke impacts on ambient air quality, therefore, further research is necessary to improve CTM simulations. **The second scope (S2) of this work is to use CTM ensemble simulations to determine wildfire smoke contributions to local air quality using source apportionment techniques.**

Pollutants from wildfire smoke, such as particulate matter (PM), nitrogen dioxides (NO_2), volatile and semi-volatile organic compounds (VOCs/SVOCs), lead to primary and secondary pollutants during transport, resulting in significant negative impacts on local and downwind air quality once they are released to the atmosphere[28]. It had been shown that urban air quality decreased significantly due to the transport of aerosols from wildfires, leading to millions of dollars of economic loss[29, 30]. A fast-response, real-time tool is needed to provide not only current air quality levels but also identify the air quality impacts from wildfire smoke. Such a tool will help estimate the wildfire-related smoke exposure risk on human health and can be used for public health alerts during fire seasons. Additionally, this tool can be used in retrospective air quality analysis to assist in identifying which National Ambient Air Quality Standards (NAAQS) exceedance days have contributions from wildfire smoke. **The last scope of this work (S3) is to develop a fast-response tool to identify NAAQS exceedance days with large contributions from wildfire smoke.**

2.B Basis and Rationale

This work will address current uncertainties in investigating wildfire smoke impacts on ambient air quality in the western U.S. This work improves the simulation of vertical distributions of wildfire smoke over mountainous areas and improves method to quantify the wildfire smoke contributions to ambient air quality. A reliable, fast-response tool will be developed to better identify the NAAQS exceedances and the influence of wildfire emissions on ambient air quality. Specifically, this work will address the UDAQ goals and priorities of:

1. Methods to improve modeling of wildfire events (transport, plume rise and emissions)
2. Approaches for quantifying the contribution of wildfire emissions to local concentrations

3. Approaches for accurately identifying if locally-monitored exceedances are influenced by emissions from wildfire events.

While the primary focus of this work is to address challenges associated with modeling wildfire smoke events, the modeling will also benefit the UDAQ priorities related to summertime ozone formation along the Wasatch Front. Specifically, the chemical transport modeling used to simulate the regional smoke transport will require testing and evaluation to ensure that the anthropogenic emissions and numerical weather prediction (NWP) modeling are correct. The source oriented CTM source apportionment can also identify which source categories are contributing to elevated ozone pollution along the Wasatch Front. Along the same lines, the results can also be used to test the NO_x-VOC sensitivities by source category to identify uncertainties in the emissions inventory for the ozone precursor emissions.

2.C Preliminary Results

This work will leverage our previous and current research to improve regional smoke transport modeling in the western U.S. Our past research has investigated the utility of satellite aerosol products to estimate surface pollution concentrations[31-34]. Where heterogeneous surface characteristics, mountainous terrain, and complex aerosol mixtures (including wildfire smoke) impact the usability of satellite retrievals in this region.

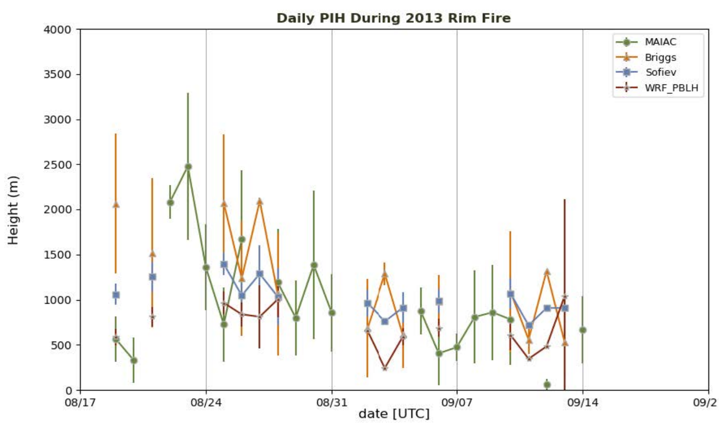

Figure 2. *Daily plume height from satellite (MAIAC) and two plume rise models used in CTMs (Briggs & Sofiev).*

Currently, we are evaluating existing plume rise models and satellite plume injection height (PIH) products for large wildfires in the western U.S. Where, initial findings suggest that no plume rise model adequately captures the vertical distribution of smoke plume concentrations during these events. Preliminary results are shown in Figure 2, plume rise from two models[35, 36] are compared with the PIH from satellite remote sensing[37]. The vertical distribution of wildfire emissions is critical to CTM performance as it significantly affects the mixing, dispersion and deposition downwind of the fires.

The NWP-Emissions (2016 NEI)-CTM modeling platform has been successfully built on our high-performance computational system and applied to several studies. We have also built and evaluated a source oriented (CTM) source apportionment model. We used these atmospheric models to estimate the impact of wildfire emissions on PM and ozone pollution during the early stage of the 2016 Soberanes Fire in California. Figure 3 shows the air quality model simulation during the Soberanes Fire with/without fire emissions (i.e., brute-force source contributions). Daily average PM and ozone concentrations are shown and the contributions of wildfire smoke are also quantified using the brute force method. Throughout the western states, wildfire smoke account for increases of 2-4 ppb ozone and 2-3 $\mu g/m^3$ $PM_{2.5}$ during this event. The Soberanes Fire caused ~4 ppb increase in ozone and 3 $\mu g/m^3$ $PM_{2.5}$ in California.

A source-oriented CTM was also successfully used to simulate air pollution during 2016 summer in the continental U.S., shown in Figure 4. Figure 4 illustrates the simulation of ozone

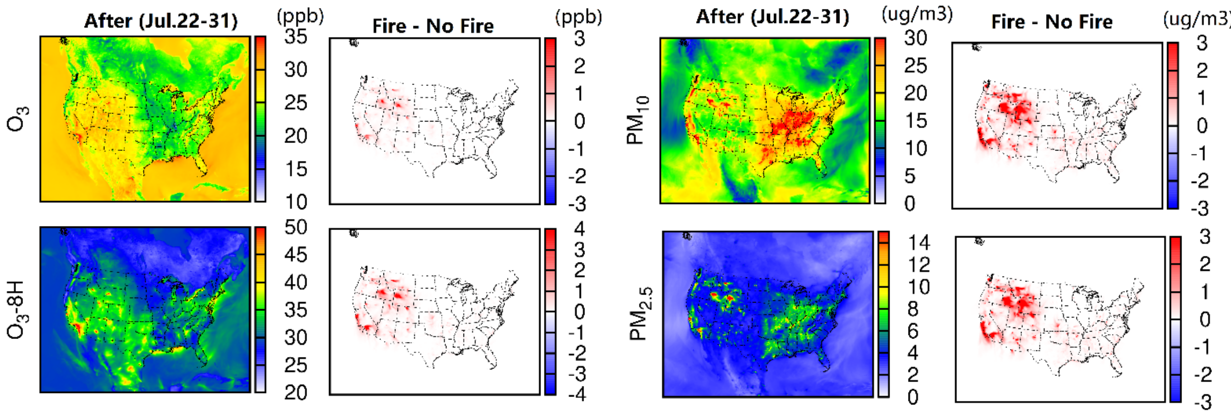

Figure 3. *Average daily air pollution concentrations of ozone and PM from CTM using the brute-force technique to identify smoke contributions during the 2016 wildfire season (California Soberanes Fire).*

source impacts during summer 2016. This simulation successfully estimates the ozone contributions due to background concentrations (BG) and different emissions scenarios (e.g., total emissions (EM) and wildfire emissions (Wildfire)). It also identifies the contributions from different ozone precursors (NO_x (O_3-N) and VOCs (O_3-V)). NO_x is the major dominant precursor while VOCs have a strong affect in south California. Wildfire emissions contributions to ozone formation range from 0.5 to 2 ppb throughout the domain. Though we successfully developed a validated the CTM source-oriented model, there are uncertainties associated with the chemical mechanisms and emission inventories. Thus, an ensemble approach would provide a more robust range of simulation results to investigate the impact of wildfire smoke plumes on ambient air quality concentrations.

2.D Technical Approach

This work will use NWP-CTM models to quantify the impacts of wildfire smoke, both locally and from long-range transport, on ambient air quality in Utah. The modeling domain will cover the western U.S. (12km horizontal resolution) and include a smaller 4km resolution

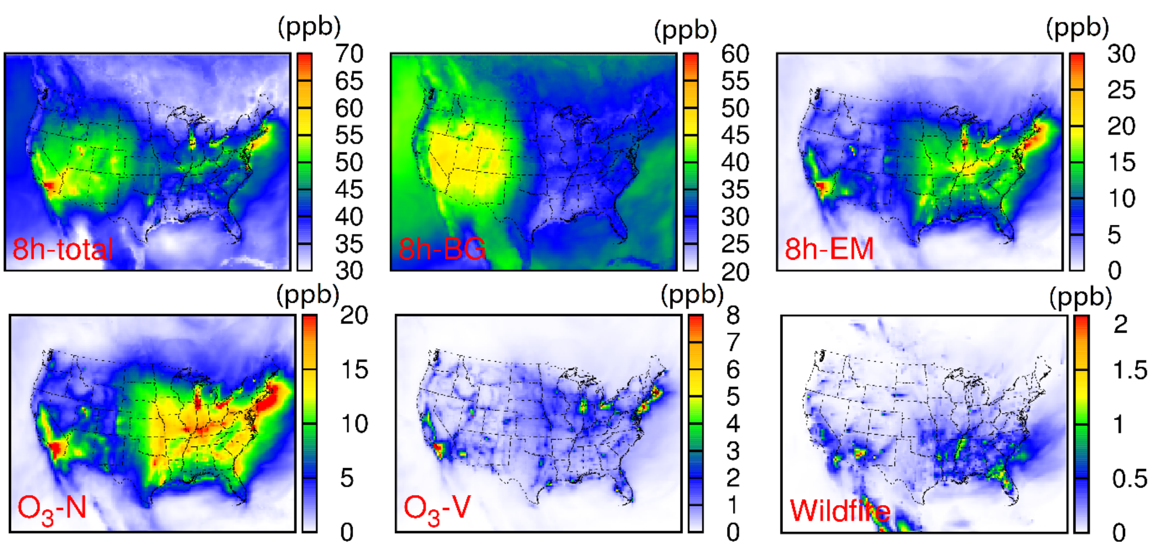

Figure 4. *Summer 2016 CTM source apportionment of ozone: BG=background ozone, EM= ozone from all emissions, O_3-N and O_3-V = contribution of NO_x and VOCs. The right bottom panel represents Wildfires.*

domain for wildfire case studies. Fifty vertical levels, with increased resolution from the surface up to 5km, will be used to improve the PBL modeling over mountains. Two fire seasons will be simulated (2016 and 2018) to provide source oriented source apportionment results for large wildfires upwind of Utah (2016 & 2018) and local Utah fires (2018). In addition to investigating the smoke impacts on air quality in urban areas, these results will be used to develop a fast-response smoke identification tool. More recent years (e.g., 2020-2021) are not used for the atmospheric modeling due to the large uncertainties in the anthropogenic emissions from COVID related shutdowns and emissions changes. Because the fast-response tool does not rely on anthropogenic emissions estimates, it will be applied to a ten-year dataset (2011-2021) from monitors in Utah to quantify smoke impacts.

2.D.1 Plume Rise Model (S1)

Objective: Develop a new plume rise model to simulate the plume injection height for large wildfire events typical of the western U.S. to improve simulations of smoke transport and downwind pollutant concentrations.

Approach: The primary focus for Scope 1 (S1), is to implement an updated plume rise model in the CTM and emissions modeling framework using assimilated data from satellite retrievals. Fire radiate power (FRP) from the NOAA GOES series satellites will be used to improve the estimates of plume buoyancy based on its higher temporal resolution (e.g., every 15min versus twice daily for MODIS)[38]. Plume rise algorithms rely heavily on the fire intensity to estimate the smoke plume buoyancy, so improved inputs for this parameter are critical to improving the plume rise model. Hourly GOES FRP will be used to estimate fire intensity and improve the plume rise algorithms in the Sparse Matrix Operator Kernel Emissions (SMOKE) model[39]. Meteorological conditions will be simulated with the Weather Research and Forecasting (WRF) model. Initial and boundary conditions will come from the North American Mesoscale (NAM) model[40]. WRF parameterizations will include Morrison 2-mom[41] Microphysics scheme, long/shortwave radiation will use RRTM and Dudhia, respectively[42, 43]. The Pleim-Xiu land surface model, ACM2 PBL scheme and Pleim-Xiu surface layer physics will be used to model the surface turbulence and PBL[44-47]. We have used this WRF configuration previously to simulate summertime atmospheric conditions in the western U.S.[31-34]. The hourly FRP and meteorological conditions will be used to model the smoke plume rise. Sensitivity testing with existing plume rise models (e.g., Sofiev[35, 36], Briggs[36]) will be done to select the algorithm that best represents fires in the western U.S. The final plume rise model will be implemented in SMOKE.

Evaluation: The updated plume rise model will be evaluated based on data obtained from multiple sources including satellite products, monitoring stations and aircraft. Multi-Angle Implementation of Atmospheric Correction (MAIAC) and NOAA GOES-16 will provide plume injection height products for evaluating the plume rise model performance. Observations from ground based LIDARs and aircraft field campaigns will also be used to evaluate the vertical distributions of smoke from the new plume rise model. The air pollution concentrations simulated from the CTM using the new model will also be evaluated using EPA monitoring data in the western U.S. to investigate the effects of the updated plume rise model.

2.D.2 Wildfire Smoke Impacts on Air Quality (S2)

Objective: Determine wildfire contributions to local air quality using an ensemble of atmospheric models and source apportionment techniques.

Approach: Numerical models will be applied in Scope 2 (S2), specifically, NWP and CTM models as well as emissions estimates using. Emissions from anthropogenic and biogenic sectors will be obtained from National Emission Inventory (NEI). Wildfire emissions will be obtained from different sources, such as Fire Inventory from NCAR (FINN) and NEI, and will be modified based on satellite retrievals to improve their accuracy. Based on the model evaluation findings, modifications will be considered for anthropogenic and biogenic emissions if necessary. Meteorological conditions will be simulated using WRF (detailed in S1 above). For the CTM, the Community Multiscale Air Quality (CMAQ) model will be used to simulate the chemical and physical transport processes of wildfire smoke and investigate the impacts of wildfires on air quality. Several source sensitivity methods and source apportionment techniques will be applied to quantify the impacts of wildfire emissions on downwind air quality. The Brute Force (BF) method will be applied to estimate the direct wildfire impacts on primary PM. The Decoupled Direct Method (DDM) is implemented in the CMAQ model (CMAQ-DDM) to evaluate the sensitivity of responses of pollutant concentrations to perturbations in emissions. Semi-normalized sensitivity coefficients are calculated to indicate the impacts during atmospheric processes[48]. The Integrated Source Apportionment Method (ISAM) CMAQ model[49] tracks tags from different grouped classifications in emissions during both chemical and physical transport processes in the atmosphere and indicates the contributions of different sources. CMAQ-DDM and CMAQ-ISAM will be applied to estimate the wildfire impacts on both primary and secondary PM concentrations.

An updated source-oriented CMAQ model, which involves reactive tracers (atomic oxygen, O(3P)) that are created in photochemical reactions tagged for ozone precursors that have been implemented in the SAPRC99 chemical mechanism, will be applied to specifically identify the ozone contribution from wildfire emissions. NO_2 and NO are tagged for tracking the atomic oxygen through NO_x-related reactions while reactive hydrocarbons (*RH*) are tagged for VOCs as shown in Equations 1-4 (E1-4), *n* represents different emissions sources. As a result, contributions from source *n* can be estimated. This improvement can be used to investigate not only the contributions from wildfires but also the potential effects of interactions between urban emissions with wildfire smoke plumes.

$$NO_{2_n} \xrightarrow{hv} NO_n + O(3P)_n \,, n = 1,2,3 \ldots, N \qquad \text{(E1)}$$

$$O(3P)_n + O_2 \rightarrow O_{3_n}, n = 1,2,3 \ldots, N \qquad \text{(E2)}$$

$$RH_n + HO \rightarrow RO_{2_n} + H_2O, n = 1,2,3 \ldots, N \qquad \text{(E3)}$$

$$RO_{2_n} + NO \rightarrow NO_{2_n} + RO_n, n = 1,2,3 \ldots, N \qquad \text{(E4)}$$

Current state-of-the-art atmospheric models have a significant amount of uncertainties in simulating the physics and chemistry of smoke plumes. Therefore, ensemble predictions will be conducted based on source analysis results from the above simulations to provide a more accurate estimation of the wildfire smoke source apportionment. In addition, the ensemble predictions will also use multiple chemical mechanisms to minimize the bias from the simulations. Mechanisms include the Statewide Air Pollution Research Center (SAPRC) chemical mechanism, Carbon Bond 6 (CB6), Regional Acid Deposition Model (RADM) and Regional Atmospheric Chemistry Mechanism (RACM). Uncertainties from emission inventories are also expected to be reduced using the same ensemble technique, incorporating emissions estimates from NEI and FINN. It should be noted here, that improvements from the first scope

(S1 above) will be applied in this scope to provide improved smoke plume simulations. Ensemble groups will be designed according to the information in Table 1 to minimize the bias from different sources and all quantify their potential uncertainties.

Table 1 Scenario design for ensemble CTM simulations.

Scenario ID	Chem Mech*	Emis Inv**	SA Tech***
1	SAPRC-07, CB-6, RADM, RACM	NEI	Source-oriented CMAQ
2	CB-6	NEI, FINN	Source-oriented CMAQ
3	CN-6	NEI	BF, CMAQ-DDM, CMAQ-ISAM, source-oriented CMAQ
4	SAPRC-07, CB-6, RADM, RACM	NEI, FINN	BF, CMAQ-DDM, CMAQ-ISAM, source-oriented CMAQ

** Chem Mech: Chemical mechanism used in CTM*
*** Emis Inv: Wildfire emissions inventory used in CTM*
**** SA Tech: Source apportionment technique*

Evaluation: Model simulations of air pollution concentrations will be evaluated using observations from the EPA monitoring networks (i.e., AQS) and local air quality monitoring programs (i.e., UDAQ). Data from meteorological networks (e.g., MesoWest) will be used to evaluate the local meteorology simulated from WRF. Statistical metrics will be applied to evaluate the WRF/SMOKE/CMAQ model performance. Based on the model evaluation, necessary adjustments will be made to WRF, emissions or CMAQ. The accuracy of the source apportionment results will be able to be directly evaluated because there are no available supportive data. However, the results from the updated source-oriented model will be compared with other source sensitive/apportionment results to qualitative evaluate the model performance. Final source apportionment ensemble simulations will be applied to assess the wildfire impacts on local air pollution concentrations.

2.D.3 Exceptional Events Tool (S3)

Objective: Develop a fast-response tool to identify NAAQS exceedance days where elevated ambient pollution concentrations have large contributions from wildfire smoke.

Approach: Data assimilation using NWP-CTM simulation results and air quality observations will be applied in Scope 3 (S3) to train a fast-response tool that is can identify the contributions from wildfire smoke. The fast-response tool will use artificial neural network (ANN) and machine learning techniques and will be programmed in Python. This tool involves two models. The first model is to determine whether the $PM_{2.5}$ and ozone NAAQS exceedances are associated with wildfire smoke. The second model is to quantify the impacts from wildfire emissions and smoke transport. In the first model, Random Forest (RF), a machine learning algorithm that is widely used in modeling air pollution issues, will be applied to solve regression and classification problems[50-52]. Source apportionment results from S2, satellite retrievals and air pollution observations during the 2016 fire season will serve as the training data to develop (i.e., train) the RF model. Training data will be used to construct decision trees that train the RF model and estimate the outcomes of wildfire smoke impacts. The number of decision trees and the explanatory variables are decided based on the corresponding dataset size. The trained RF model will provide an index that classifies whether or not wildfire smoke contributions to the local air pollution concentrations.

The second model will use ANN, which has successfully been used in air pollution studies, to quantify the air pollution impacts from wildfires[53-55]. This model will be trained based on the RF results for the NAAQS exceedances because the air quality on those days are associated with wildfire emissions. The ANN training data will include air pollution observations, source apportionment estimates (from S2), fire intensity, distance to fire, wind direction/speed, temperature and humidity. Sensitivity testing varying the number of nodes and will be done to determine the best configuration of the ANN model. Results will be evaluated, and the final best performing model will be used to establish the fast-response tool.

Data from the local monitoring network and EPA will be used to provide air quality data, including concentrations of PM (PM_{10} and $PM_{2.5}$), ozone, NO_x, and CO, for this work. Fire information, including fire intensity (FRP), location (distance from monitoring station to fire), duration and fire emissions (PM, NO_x, VOCs and CO), will be obtained from NEI and satellite retrievals. Meteorological conditions will come from surface stations. Simulations of the 2016 and 2018 summertime air quality and source apportionment results (from S2) provide detailed wildfire contributions to local air quality for training the models. In this regard, half of the NAAQS exceedance days will be classified as the training dataset to train the models and the remaining will be used to test the RF & ANN model performance.

Evaluation: Because there are no direct supportive data to evaluate smoke plume concentrations the source apportionment results from S2 will be used to evaluate the results from this novel, fast-response tool. Excluding training data, the 2016 and 2018 summer datasets will provide the air pollution contributions from wildfire smoke from the CTM source apportionment simulations. Testing with different sets of model configurations using RF and ANN will be done to develop this tool and the results from different scenarios will be compared with results from S2. The final model configuration will be used to establish the fast-response tool to classify exceedance days (retrospective analysis) and provide smoke alerts (near real-time analysis).

2.E Expected Outcomes

A new plume rise model is expected from the first scope (S1) to improve the vertical distribution of smoke plume concentrations for emission modeling. This updated plume rise algorithm will be implemented in the SMOKE and CMAQ models to reduce the biases when simulating wildfire smoke transport over mountain areas. Results from this objective will help to better estimate the air quality impacts in Utah during fire season.

The second scope (S2) is designed to provide a reliable simulation of summertime air quality in Utah and estimate the wildfire smoke contribution to the local ambient air pollution concentrations. These results can be used to evaluate the wildfire smoke impacts on human health, including the associated economic losses. In addition, the findings from this work will be used to support the next scope in our study.

Scope three (S3) will develop a quantitative tool in Python to identify the influence of wildfire smoke on ambient pollutant concentrations using monitoring data. With improvements in the plume rise model and source apportionment results, a reliable tool that leverages machine learning techniques will be developed. The tool will identify wildfire impacts on local air quality by directly extracting observation data and wildfire information. This tool will be designed to provide real-time quick-response detections of wildfire smoke.

2.F Deliverables

Completion of this work will help local analysis and alerts for wildfire smoke impacts on air quality. The first scope is to reduce biases in estimating smoke plume transport over mountains which is the dominant terrain in Utah. This achievement provides a new, tested plume rise model to better estimate wildfire emissions and detailed transport processes which can be used to forecast both short- and long-term effects from wildfire. The second scope is to improve estimations of the source impacts of wildfire smoke to ambient air pollution in Utah. Achievement of this scope provides an effective source apportionment model to tracing both the PM and ozone formation due to wildfire emissions. This will help UDAQ better quantify wildfire smoke impacts on Utah air quality and support further estimates of health risks and economic losses from smoke. The fast-response tool from the last scope will help UDAQ by assisting with identifying wildfire smoke contributions to NAAQS exceedance days and aid in developing a public alert system for wildfire smoke. Overall, this project will provide a deeper and clearer understanding of the wildfire smoke impacts on air pollution in Utah.

This work will be completed in one year with quarterly reports and a final report to UDAQ. Simulation results and data will be freely available to anyone on the PIs website. Code modifications and tools developed will be publicly available on GitHub and shared with UDAQ. If additional data is requested, it will be made freely available to any interested party upon written request to the lead researcher within 10 years of project completion. The research personnel plan to present data in academic venues including workshops, publications and professional conference events. Including the Utah Air Quality: Science for Solutions conference.

The PI has Utah High Performance Computing (CHPC) resources, including a large amount of data storage available (over 100TB). Funds are requested in the budget to purchase long-term data storage on CHPC to be dedicated solely to this project. This will provide reliable data storage and archiving for at least 10 years following the completion of this project. The information stored will primarily be model simulation and machine learning codes (which will also be made available via GitHub) and model simulation results.

2.G Schedule

This work will be completed in one year (7/01/2022-06/31/2023). A quarterly timeline (Q1-4) with the scopes (indicated by S), major deliverables, reports (indicated by R) and publication submission (indicated by P) are listed in Table 2. Results from this project will be presented at the Air Quality: Science for Solutions annual conference in Spring 2023.

Table 2 Task Timeline (7/01/2022-06/31/2023)

Deliverables	**Q1**	**Q2**	**Q3**	**Q4**
Data collection, preliminary analysis	R1			
S1: Improve smoke plume rise model		R2		
S2: Quantify wildfire impacts on air quality			R3	
S3: Develop a wildfire smoke identification tool				R4/Final
GitHub CTM code modifications (S1/S2)				
GitHub Wildfire smoke detection code (S3)				

Science for Solutions conference presentation				
Prepare publication summarizing findings				P

3. Budget

A budget for the one year project is provided in Table 3, budget justification follows.

Table 3 Detailed Budget Information

	Scope 1	Scope 2	Scope 3	Total
Personnel				
Kaiyu Chen @ $60,000/yr for 6 mo. (0.5 FTE)	$10,000	$10,000	$10,000	**$30,000**
Jingting Huang @ $31,000/yr for 3 mo.	$7750	$0	$0	**$7,750**
Fringe benefits Research Associate (52%) Grad Student (10%)	$5,975	$5,200	$5,200	**$16,375**
Supplies				
Hard disk storage				**$450**
Other				
Publication fees				**$1,500**
Science for Solutions Conf. Fee				**$50**
Total direct costs				**$56,125**
Total indirect costs (10%)				**$5,613**
Total project cost				**$61,738**

3.A Budget Justification

University of Utah is on a 9-month academic and 3-month summer calendar schedule.

Personnel

Project PI, Dr. Heather Holmes, is not included in the budget but she will devote time to the project to advise the Research Associate and Graduate Student. This aligns with her current tasks and funded projects as an Associate Professor in Chemical Engineering at the University of Utah, therefore, she does not require salary support.

Research Associate, Dr. Kaiyu Chen, is budgeted at 0.5FTE over the one year project with an annual salary of $60,000. Dr. Chen is currently working in the PIs research group on wildfire smoke and air quality modeling projects and is funded for the remainder of the FTE on those projects. Dr. Chen will devote 50% effort to this project to develop new software and code modifications for air quality modeling, biomass burning emissions, wildfire smoke transport modeling, and machine learning tools for air quality characterization. This includes modifications to the wildfire emissions inventory, adding the plume rise code in a chemical transport model and implementing the machine learning algorithm to forecast fire emissions and air quality.

PhD Student, Jingting Huang, is budgeted for three summer months with an annual graduate student salary of $31,000. Jingting will devote 100% effort to this project over the three months to collect satellite remote sensing datasets related to wildfire and smoke characterization and test smoke plume rise models. This includes collecting and combining all relevant satellite products, developing a new plume rise model, and working with Dr. Chen to add the plume rise code into the chemical transport model.

Fringe Benefits

Fringe benefit rates are 52% for research associates and 10% for graduate students.

Other Direct Costs

Supplies: Project specific supplies are budgeted at $450 to purchase hard disk storage.
Publication Costs: Page charges for one publication is included at $1,500.
Conference Fee: Fee for the Research Associate and Graduate Student to attend the Utah Air Quality: Science for Solutions conference, $25 for each.

Total Direct Costs

$56,125

Indirect Costs/F&A

UDAQ has a limit on the indirect cost rate, these were calculated at 10%; $5,613.

4. Personnel Roles and Responsibilities

The majority of this work will be led by **Dr. Kaiyu Chen** who is a Research Associate in the Department of Chemical Engineering at the University of Utah. Dr. Chen has more than five years of experience working with the WRF/CMAQ modeling system and has more than 12 publications related to air pollution and source apportionment of PM and ozone. Specifically, for Dr. Chen's Ph.D., he successfully applied the source-oriented CMAQ model to investigate the ozone pollution contribution to different emissions sources in the both continental U.S. and southeast U.S. He used these results to estimate the potential health risk to humans. Dr. Chen will apply his knowledge of air pollution and skills in modeling and analysis of pollution concentrations to achieve the goals of this project.

Scope 1 will be completed with assistance from **Jingting Huang.** Jingting is a Ph.D. candidate in the Department of Chemical Engineering at the University of Utah and has a MS in Atmospheric Sciences from the University of Nevada, Reno. Jingting has more than four years of experience using remote sensing products to study clouds, aerosols and wildfire smoke plumes. Her previous research used analytical radiative transfer models to quantify uncertainties in aerosol remote sensing products. Jingting will be responsible for developing the novel smoke plume rise model for this project, using on her skills and knowledge of atmospheric models and data assimilation of satellite remote sensing products.

This project will be supervised by **Dr. Heather Holmes** who is an Associate Professor in the Department of Chemical Engineering at the University of Utah. The focus of her research group is both numerical and experimental air quality applications, including regional air quality modeling, transport and dispersion of atmospheric pollutants, and the impact of air pollution on human health. She has a strong track record of collaborating with biostatisticians and heath scientists to study the impacts of air pollution exposure. Dr. Holmes' knowledge of numerical modeling and applications of satellite remote sensing products, especially in the western U.S., will provide expert guidance to this project.

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